Developing Deep Neural Network Models for Prediction and Prognosis of Head and Neck Cancer

SHORT SYNOPSIS

Submitted in partial fulfillment of the requirement of the degree of

DOCTOR OF PHILOSOPHY

To

Manav Rachna University

By

Deepti
Registration number: 2K19-PFE-010

Under the supervision of

Prof. Susmita Ray

Designation: Professor

Department of Computer Science and Engineering

MANAV RACHNA
vidyanatariksha

MANAV RACHNA UNIVERSITY
(FORMERLY MANAV RACHNA COLLEGE OF ENGINEERING
NAAC ACCREDITED 'A' GRADE INSTITUTION)
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DECLARATION BY THE SCHOLAR

I hereby declare that the short synopsis titled "**Developing Deep Neural Network Models for Prediction and Prognosis of Head and Neck Cancer**" being submitted in partial fulfillment of the requirement for the degree of Doctor of Philosophy in department of Computer Science and Engineering under Faculty of Computer Science and Engineering of Manav Rachna University, Faridabad during the academic year 2019-2020.

It is a bona-fide record of original work carried out under the supervision of Prof Susmita Ray and has not been submitted in full or part to any other university or institute for degree or diploma. Further, it is certified that short synopsis is within the plagiarism limit and copy of the same is attached as per University norms.

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ABSTRACT

Machine learning has provided a capability to learn from past experience and take decision for upcoming tasks. Machine learning with its advancements is showing very promising results in many real world applications including medical domain. Availability of automated systems in health care especially in cancer classification, prediction and prognosis estimation has become possible with the application of machine learning algorithms. Very extensively skilled and experienced practitioners are required for complete manual evaluation of all the biomedical data for cancer prediction and diagnosis. With the developments in hardware technology and imaging data availability, neural networks are showing very good results in automated learning from previous datasets and generating automated systems for cancer prediction and prognosis to help medical practitioners in decision making. The neural networks with deep layers, also known as deep neural networks are expected to extract features and learn with better accuracy. Recently a lot of research is carrying out in various common occurring cancer like kidney, prostate, lungs and oral cancer. Our proposed work aims at applying deep learning in radiological data of Head and Neck cancer region and achieving a good accuracy for prediction and prognosis in same. Radiomics is an upcoming field of extracting complex high dimensional features from medical images like CT scans, PET(Positron Emission Tomography), HSI(Hyper spectral Images), MRI images, Ultrasound, CLE (Confocal Laser Endomicroscopy. These extracted features can be used to train a model for prediction and prognosis puposes. The most powerful ability of deep convolutional neural network is to extract multiple features. The training time can be reduced by applying a pre trained network to fine tune our given task of prediction and prognosis.

Keywords: machine learning, deep learning, transfer learning, imaging datasets.

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1. INTRODUCTION

Recently, one of the worldwide leading health problems is Cancer. Cancer can attack any site of the human body. Majority of the reported cancer cases are of breast, lungs, prostate, kidney. Recently there is an increasing graph of number of patients in head and neck cancer. Cancer effects financial, physiological and psychological state of patient. That's why to strengthen critical decision making and have reasonable result expectations, it is very beneficial to have a good automated system for predicting prognosis. An automated system for cancer prediction and prognosis is used to help medical practitioners in taking treatment decisions and personalized medicines. A cancer prediction and prognosis model is expected to provide any of three types of outcomes. These are cancer susceptibility, cancer reoccurrence prediction, survivability prediction. Cancer susceptibility is to predict the probability of occurrence of a type of cancer in advance to its occurrence. Cancer recurrence is to predict the probability of regeneration of the cancer post treatment and management. Life survivability is to predict life expectancy, survivability, progression, tumor-drug sensitivity. Prognosis result has a great impact on treatment plan.

Along with detailed cellular and genomic study of patient other factors like age, sex, weight, family history, specific habits, contact with carcinogenic chemicals , demographic factors play a role in cancer prevention and risk assessment prediction. With the advancement in medical imaging technologies, high resolution images are available for better grasp of the molecular and tissue changes. Quantitative imaging features are able to provide substantial details about size, shape, intensity, volume and texture of tumor constitution using variable imaging techniques. It is subjective decision and requires a lot of experience to be able to extract the complete rich set of information from these images. To extract these quantitative features from various medical images is called radiomics. Radiomics is the application of appropriate machine learning algorithm to imaging data set to extract features to analyze and provide predictive and prognostic information.

Recently, machine learning is vastly used in medical domain. Machine learning algorithms have the capability to provide an automated system to predict classification, recurrence, prognosis of the disease based to previous data. Various machine learning techniques majorly decision tree, support vector machine, KNN have been applied on clinical data. With the availability of imaging data like CT scans, MRI scans, PET scans Convolution neural networks have shown more promising results.

A deep neural network is a network having multiple layers and have shown promising results by automatic feature extraction. These extracted features can be analyzed by various machine learning techniques to provide prediction and prognosis system.

2. Literature Review

The efficiency of machine learning in Prediction and Prognosis of cancer is evident with the increase in availability of various Scopus and pubMed published articles regarding application of machine learning for prediction of cancer survivability, susceptibility and cancer recurrence.

From early years of research, K-nearest neighbor, Support Vector Machine, Decision trees, Naïve Bayes, Neural Networks were majorly for Cancer prediction and Prognosis puposes. As reported in recently published papers, the latest developments in Deep Learning and availability of high resolution images dataset led to the application of these algorithms in cancer prediction and prognosis. Initial researches were done with the implementation of conventional statistical methods but with the evolution in machine learning, researchers have gained the facility for statistical analysis of the inter-related heterogeneous data from different resources.

According to most of the well-known published articles, data deficiency is a problem in prediction purposes. Data deficiency deals with low number of instances and high number of attributes i.e features. Some of the attributes may not be apt for the given system.

Analysis results greatly depend upon quality of training data. Too few or too more variables generates the situation of curse of dimensionality, that is to have uncertain results. Data needs to be prepared to analysis. Cancer is a heterogeneous type of disease as there is a phenotypic and genetic diversity in same or different type of cancer. There is an involvement of multiple complex inter related features according to the cancer effected organ site and type of cancer for its depiction. Such a complicated and high amount of features are exhibited by histological images that they may remain unnoticed by even a well skilled and experienced practitioner, so it is beneficial to have an automated support system for feature extraction and classification purposes. Classification and data mining tools can be used to extract the most important features for a particular type of cancer. Recent researches show that Deep learning can conquer the problem of heterogeneity in cancer type.

Pegah et al. implemented CNN algorithms on heterogeneous dataset of cancer in lungs , breast and bladder. The model was proposed to distinguish different cancer types, and its subtypes with Immunohistochemistry markers and their expression scores. The dataset used was a combined dataset from repositories of TMAD, open access histopathology images and TCGA. Different accuracies were reported on different types of cancer with different type of architectures. The accuracy is measured in terms of area under ROC curve. The accuracy of cancer subtype detection varies with the type of selected dataset, tumor heterogeneity and algorithm architecture, and ranges from 61% to 100%. Separation of various types of bladder IHC markers resulted in 71.5% to 99% accuracy and breast IHC markers showed 79.2% to 90% accuracy.

Fatihah Mohd et al. designed a model to predict the oral cancer stage with 14 features. Originally, 25 features were recognized, later on these features were reduced to most relevant 14 features by hybrid feature selection methods. To classify the staging in oral cancer dataset further four classifiers were implemented namely SVM, Naïve Bayes, Multilayer perceptron, KNN. Further SVM was implemented with feature subset selection with Synthetic Minority Oversampling technique at preprocessing phases to overcome the problem of data skewedness. Data skewedness refers to class imbalance as one type of data is in more abundance than others. In the given study, to solve the issue of imbalance in data classes, the SMOTE algorithm is integrated with diagnostic model. This study was carried out on 25 features and 82 instances or records. The 25 features comprised of primary stage features, demographic features, and histological-pathological features clinical signs and symptoms. The initial data set of 82 instances was classified into four stages. These are :majority class with 58 instances of the stage four, minority class with less than 10 for stage 2 , 16 instances for stage three, and 16 instances for stage one. The efficiency of feature selection classifier in the form of accuracy is summarized as given below:

Classifier used	Without SMOTE	With SMOTE
Naïve Bayes	87.80%	94.76%
Multilayer perceptron	90.24%	95.24%
SVM	86.59%	96.20%
KNN	76.83%	91.43%

Table1. Accuracy improvement with feature reduction through SMOTE

Michele Avanzo et al studied the application of CE-CT and PET images for radiomics driven models for prediction in distant metastasis, survival expectancy, side effects prediction, molecular targeted therapy, immuno-therapy, classification of benign and malignant tumor, local control, response and recurrence. This study concluded that various challenges with radiomics is interpretability, repeatability, reproducibility. Repeatability is feature extraction with repeated possession of images in same conditions whereas reproducibility is eaxtraction of features with different parameters.

Lavanya L et al. worked on oral leukoplakia dataset for staging prediction of Oral squamous cell carcinoma using various machine learning algorithms including SVM, decision tree, K-nearest neighbors, Multilayer Perceptron, random forest and Logistic regression to classify extracted features. Various experiments so far have done on classification of cancer type, prediction of cancer presence in a tissue. This study works on predicting tumor stage as it will determine further treatment planning. Decision Tree and Random Tree showed best accuracy results. Accuracy rate of various classifiers is shown in table below :

Decision tree	90.688%

Random Forest	91%
SVM	88%,
KNN	85%
MLP	81%
Logistic regression	80%

Table 2 : Accuracy chart of various classifiers for stage prediction on OSCC dataset.

To classify the type of Head and Neck cancer, Olatunbosun Olabode et al implemented KNN and decision tree. The data set used were total 1473 instances with 18 features of four classes of cancer i.e. sino-nasal cancer, thyroid cancer, nasopharyngeal cancer and laryngeal cancer. According to the observations, the F1 score and accuracy result for KNN was 0.8894 and 88.24% respectively whereas Decision Tree has F1 score of 0.9054 and accuracy result of 91.40%.

Mete et al. detect presence of tumor and distinguishing cancerous cells from healthy cells. Using virtual histological slides, density based clustering algorithm is used for feature extraction on equal sized images, obtained by partitioning of original slides. It is designed to detect the clusters of arbitrary shapes. Malignant regions are discovered from healthy areas by application of classification algorithm SVM with an accuracy of 96%. Quality of imaging technologies used produce challenge of reproducibility, as across different image scanners variable acquisition parameters may be used. Imaging features are also influenced by the timing and variability in contrast used.
A limited amount of records available in medical dataset with missing data values and class imbalance issues may lead to overfitting. This issue can be resolved by transfer learning concept where different pre-trained CN architectures are implemented to extract deep features, then these features are fed to another classifier for classification.

Rahul Paul et al. in an experiment on CT images of non-small cell adenocarcinoma lung cancer, applied a pretrained Convolution Neural Networks to retrieve deep features from dataset of 40 CT images. Then combine the traditional image features with the deep features and train the classifiers to predict patient's life expectancy. Along with chest CT scans, associated clinical data was used. The dataset was divided in two ranges. Long term survivors are placed in upper quartile and short term survivors are placed in lower quartile. Images of same size are cropped that closely fit the tumor from original image to prevent the side effect of missing value. A rectangular image patch from the CT scan image that completely covered the tumor is called a warped tumor. Various methods for feature selection and pre-trained Convolutional Neural Networks were implemented and tested. In previous studies best accuracy of 77.5% was reported in decision tree classifier. 90% of accuracy was achieved with feature extraction with CNN and transfer learning with traditional classifiers and the 5 best post-rectified linear unit features extracted from a vgg-f pre trained CNN. Amongst traditional algorithms the topmost results were observed with the symmetric uncertainty feature ranking algorithm and next best classifier is random forests.

Marc Aubreville et al. experimented with deep learning based Automated Classification of Cancerous Tissue in Laser endomicroscopy Images. Department of Oral and Maxillofacial Surgery (University Hospital Erlangen) collected a dataset of 116 video sequences from 12 oral cavity cancer patients. Four image sequences are retrieved from each patient. These are one from doubtful carcinogenic region and other three from other physiological regions i.e. region of the hard palate, the upper alveolar ridge and inner lower labium[14]. The data cleaning is done by first with patch extraction of images to reduce noise, second data is augmented by rotating CLE images to avoid biasing, after that classification is carried out using textural based features on LBP (local binary patterns) and GLCM (Gray-level co-occurrence matrices) . For classification SVM and random forest classifiers were used.

In second step patch feature extraction is performed using CNN based architectures. This CNN is based on the LeNet-5 network.
According to this paper, the patch probability fusion method, is proved to recognizably overshine the results from the conventional approaches like image texture-based classifiers.

Martin Halicek et al in collaboration with the pathology and surgical teams of Emory University Hospital Midtown collected 88 excised tissue samples from 50 H&N cancer patients who were undergoing surgical cancer removal and collected three types of tissue samples per patient. The first sample is from tumor tissue, next a sample from normal tissue, and then a sample at the interface of tumor–healthy tissue. These 50 patients of H&N cancer were further divided with type of cancer as, 29 patients with squamous-cell carcinoma and 21 patients with thyroid carcinoma. HIS data was normalized to compare different samples from different types of cancer. The convolution neural network architecture comprised of three fully connected layers and six convolutional layers. The patch of 10 × 10, and the convolutions of kernel size 3 × 3 is used to train the dataset. The final layer, i.e., softmax, outputs a probability of the pixel belonging to one of the two classes. Two disjoint groups were created, with random division, from the dataset of spectral patches from all 50 patients, which represents the training and testing datasets. One of the groups comprised of 75% of the spectral patches and utilized as the training dataset. Whereas the other group comprised of remaining 25% spectral patches acted as the testing dataset. Performance of CNN architecture was compared with other classifiers like SVM, KNN, LDA, LR and DTC and observed that CNN classifier outperformed these classifiers. The comparison result is shown in table below:

Classifier	Accuracy (%)	Specificity (%)	Sensitivity (%)
CNN	96.4	96.1	96.8
SVM	92.3	91.6	93
KNN	89.4	86.9	91.9
LR	81.8	82.2	81.4
DTC	79.3	72.6	85.8

Table 3 . Head and neck cancer classification results with different classifiers

Martin Halicek et al in another experiment collected dataset from Otolaryngology Department and the Pathology Department and Laboratory Medicine at Emory University Hospital Midtown and applied CNN Inception V4 CNN with whole slide imaging to classify tumor and normal tissue. The proposed method diagnosed the entire WSI with SCC with an Area under curve of 0.944 and Thyroid carcinoma WSIs were diagnosed with an AUC of 0.995.

Ling Ma et al classified head and neck tissue as normal or cancer tissue using CNN on dataset of 12 mice having tumor. The input of CNN is a patch with size 16×16 with two consecutive convolutional layers and mean-pooling layers. The first convolutional layer consists of 5×5×1 sized 12 kernels and second layer consists of 3×3×12 sized 24 kernels. The output produced by first layer is 12 blocks of 12×12 and output from second layer is24 blocks of 4×4. The convolutional layers follow mean-pooling layers. With learning rate of 1 and batch size of 50, this model achieved an average accuracy of 91.36%, sensitivity of 86.05% and specificity of 93.36%.

William Le et al. proposed and achieved a good result on a fully convolutional approach to head and neck cancer outcome prediction. CNN architecture was implemented using residual connections on combining PET and CT image inputs. Dataset used consisted of 298 HNC patients acquired from 4 different institutions in Quebec. The dataset presented only 56 (19%) cases with death record. Thus a resampling strategy with data was used to rebalance the dataset. The CNN classifier used is inspired by the ResNeXt architecture.

Yu Murakami et al developed the fully automated framework for prostate cancer dose generation intensity modulated radiation therapy by making Generative adversarial networks to extract the features of CT images. GAN‘s performance for prediction is compared with the traditional prediction framework trained from the contour information. The mean differences of all dosimetric parameters except for D98% (covered with 98% of the prescribed dose) and D95% (covered with 95% of the prescribed dose) for planning target volume were within approximately 2% and 3% of the prescription dose for organs at risks in the CT-based model.

Ling Ma et al presented an improved approach to classify tumor and benign tissue adaptively on previous studied mice model. Experiment was conducted on 12 tumor bearing mice HIS images. An auto-encoder network is trained to provide prediction for benign and cancer tissue pixel wise. It is trained to extract deep features based on the wavelength bands on hyper-spectral images. According to the assumption, misclassified pixels are reclassified. Auto-encoder network is retrained over these reclassified pixels, hence improving the accuracy in prediction of classification of benign and tumor tissue. The suggested method of adaptive deep learning for detection of cancer tissue on Hyper-Spectral Images contains four steps: data pre-processing,

deep feature learning with auto-encoder network, adaptive weight learning, and post-processing. The average value of sensitivity of 12 mice is 92.32%, average specificity is 91.31%, and accuracy of 12 mice is 92.32%. These values are higher than values from model without auto-encoder networks.

3. Description of Broad area

3.1 Machine Learning

Machine learning has the ability to learn on their own. Given with the data input, machine learning algorithm uses learning algorithm and can infer underlying relationship amongst data to make decisions. There are two types of machine learning algorithms; these are supervised algorithms and unsupervised algorithms. In supervised learning, machine learns to make decisions with the help of labeled data. Labeled data means data with input and output tags.

Input of n training examples is provided in the form {(x1,y1)(x2,y2)- - - - - - - - - - - (xn,yn)}

Such that $X = (x_1, x_2, x_3, \text{----------}, x_n)$ is feature vector

$Y = (y_1, y_2, y_3, \text{----------}, y_n)$ is label vector

Learning algorithm learns g: X->Y, g is one of the possible function from the space of possible functions G, also called hypothesis space.

Where X is input domain

And Y is output domain.

Machine learns the relationship between data points. Two types of supervised learning are regression and classification. Various classification learning algorithms are decision tree, Naïve Bayes, random forest, support vector machine, neural networks.

Unsupervised learning is to learn data relationships from unlabeled data. Cluster analysis is a type of unsupervised learning.

3.2 Neural Networks

Neural networks are supervised machine learning algorithms that simulate human brain neuron system to depict relationships between enormous data available. A neural network is a layer of perceptron. A perceptron is a single layer neuron network that takes inputs and applies algorithm for supervised learning to decide whether an input belongs to a particular class or not.

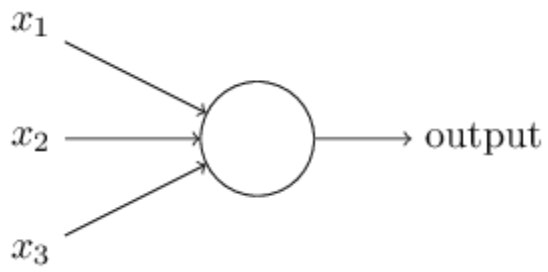


Figure: Perceptron

Here, x1,x2,c3 are three inputs, weights w1,w2,w3 representing relevant importance of given input, can be applied to these inputs. An activation function is applied to these inputs in neuron. The neuron's output can be 0 or 1 depending upon whether

the weighted sum $\sum_j w_j x_j$ is less than or greater than some threshold value.

Output=1 if $\sum_j w_j x_j$ >threshold value

=0 if $\sum_j w_j x_j$ <threshold value

This single layer perceptron can make simple decisions. For more complicated and at more abstract level decision making a multilayer neural network is used.

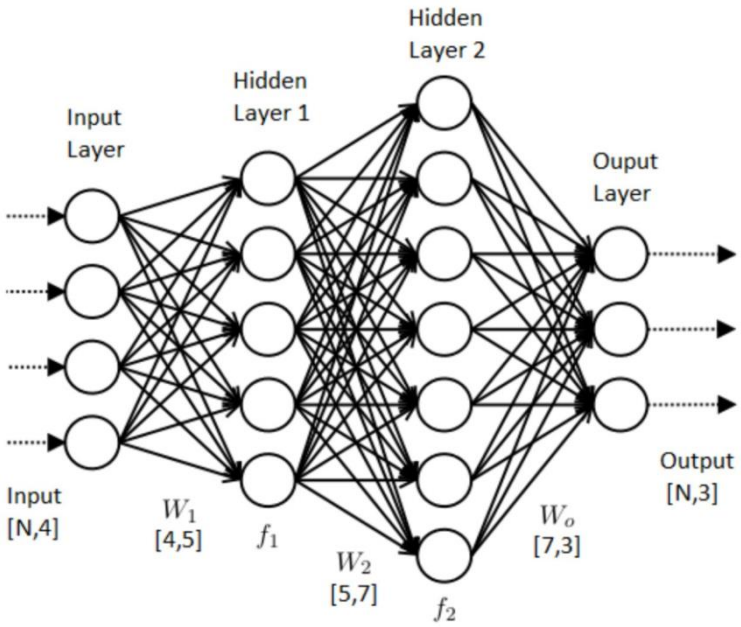
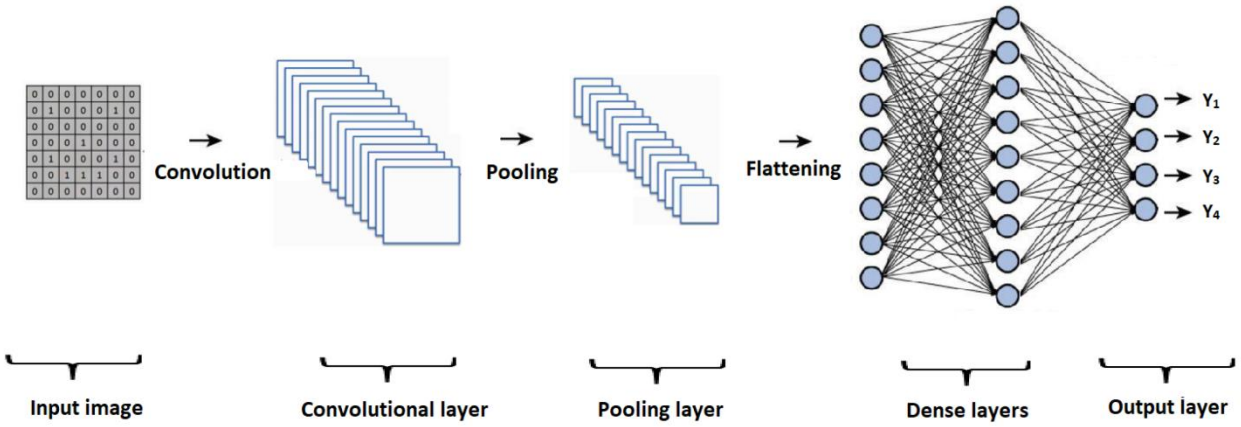


Figure: A multilayer neural network

3.3 **Convolutional Neural Network**

In 1990's an advanced type of neural network called convolutional neural network was introduced. CNN deals with pictorial data. CNN improves the machine learning performance in

image segmentation, detection, classification and retrieval related tasks. One of the greatest advantage on CNN is automatic feature extraction. Convolutional neural network is a deep learning network widely used for imaging data. The recent developments in deep learning have an attractive feature of ability to learn in both spatial and temporal domains. CNN is a feed forward multilayer hierarchical network. CNN architecture comprises of convolutional layers, non-linear processing units also called as activation function and subsampling layers. Convolutional layer performs transformations and leads to extraction of useful features. Computer images are read as pixel matrix (NxNx3) of height by width by depth. Depth is taken as 3 on account of three channels of RGB.



In convolution layer a learnable filter of MxMx3 is slided over input file to compute activation map. Here depth of original file and filter is same but height and width dimensions are reduced. The output of convolution layer is fed to non –linear activation function. A set of activation maps is produced by different filters on input image and given to next layer. The pooling layer is in between convolution layer and controls the problem of over fitting by reducing the number of parameters and hence reducing the computation of network. Last layer is fully connected layer. It is connected to all the activations from previous layer. The powerful ability of hierarchical learning and automatic feature extraction make it more suitable to make decisions regarding classification of cancerous cell from non-cancerous cells.

CNN learns with back-propagation algorithm. Its architecture adjusts its weight according to the target.

3.4 Deep Neural Networks

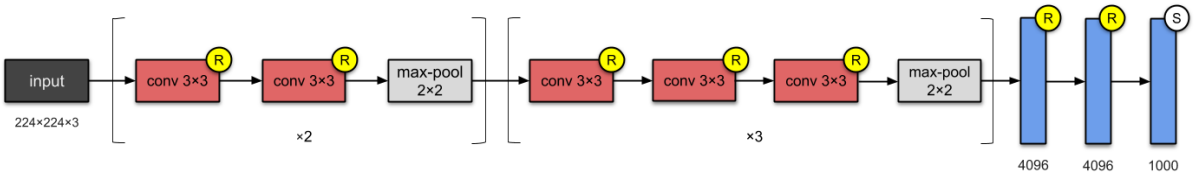
A CNN with multiple deep layers is deep convolution neural network. A multilayer deep neural network is advantageous while dealing with complex learning problems with different levels of abstraction.

Recent advancements in DNN are contributed to improvements in hardware and data management technologies. DNN's are applicable to large, complex, multi class problems. The ability to learn from complex representations of multiple images makes it advantageous to use DNN in automated cancer classification and prognosis systems. Features extracted from CNN can be transferred to generic recognition task by transfer learning.

Some of the deep neural networks are

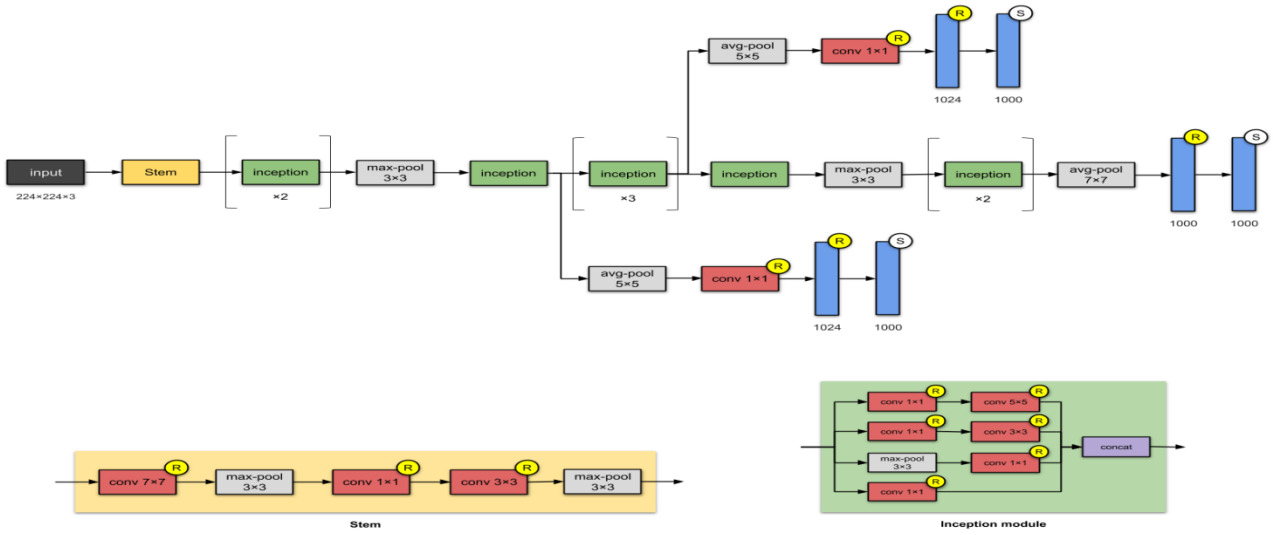
3.4.1 VGG-16

Visual Geometry Group was introduced in 2014, improved the performance of deep neural networks by increasing their size. It has thirteen convolutional layers and three fully-connected layers, ReLU as activation function. This network increased layers onto AlexNet, with the use of smaller size filters of size 2×2 and 3×3. It consists of 138M parameters and takes up about 500MB of storage space.



3.4.2 Inception-v1

It has 22 layers with 5M parameters. In this Network in Network approach is used with inception modules. It has parallel towers of convolutions with different filters.



3.4.3 Xception

Xception can be viewed as extreme Inception architecture, where the Inception modules have been replaced with depth wise separable convolutions. Inception block is widened with a single dimension of 3X3 followed by convolution of 1X1.

3.4 Deep Transfer Learning

Application of knowledge learned from one task to perform another task is called Transfer Learning. For eg. learn image processing on cats images and then apply that knowledge on X-ray scans. To train on a task is called pre-training and to apply knowledge on new task is called fine tuning. Transfer learning makes a great sense when there is a big dataset for pre trained task A and a limited dataset for tuned task B. that is there may be a case where image processing is carried out by a deep neural network with big dataset and then inferred knowledge can be applied to relatively small dataset of X-ray images. But it does not make sense for vice versa. Primary requirement for transfer learning is to have same type of inputs for both the tasks. In pretraining neural network can work as feature extractor but last layer of deep neural network is used for tuning. Task B is learned with the help of low level features from task A. It decreases the training time. So this technique can be used to tune a model for prediction and prognosis of Head and Neck cancer radiological images where features are extracted from a pretrained network.

3.5 Autoencoder

Autoencoders are unsupervised neural network compression algorithms for representation learning. In autoencoders input is same as output where input is compressed to lower dimension code and reconstructs as output. An autoencoder has three components: first is encoder to encode and generate code, second is code, third is decoder that decodes and reconstructs the output by using same code. Aoutoencoder networks are data specific as they are used to compress the data similar to what they have been trained on. These is a loss from input to output. In autoencoders the dimensionality of input and output should be same and it can have as many layers as we require**.** These networks can be used as a feature extractor for prediction and prognosis in Head and Neck cancer using imaging data.

Availability of Dataset for research

Head and Neck cancer imaging dataset is available at **The Cancer Imaging Archive** repository for datasets

4. Research Gaps

- Not much work has been done in Head and neck cancer
- More experiments on hybrid of deep feature extraction from deep learning and classification with other ML techniques can improve results.
- Fusion of radiomics features and deep features extracted through DNN can be more explored.
- Recently evolved CNN architectures can be implemented.

5. Objectives of Research

1. To study existing research work on machine learning models developed for prediction and prognosis of Head and Neck cancer and explore the possibility of application of the specific Deep Neural Networks and traditional Machine Learning Algorithms for building models to aid in prediction and prognosis of Head and Neck cancer.

2. To implement some stable Convolution Neural Networks to aid in prediction and prognosis of Head and Neck cancer

3. To implement Machine Learning algorithms on features extracted through radiomics for building models to aid in prediction and prognosis of Head and Neck cancer.

4. To apply machine learning algorithms on deep features extracted through a deep neural pre trained architecture to aid in prediction and prognosis of Head and Neck cancer.

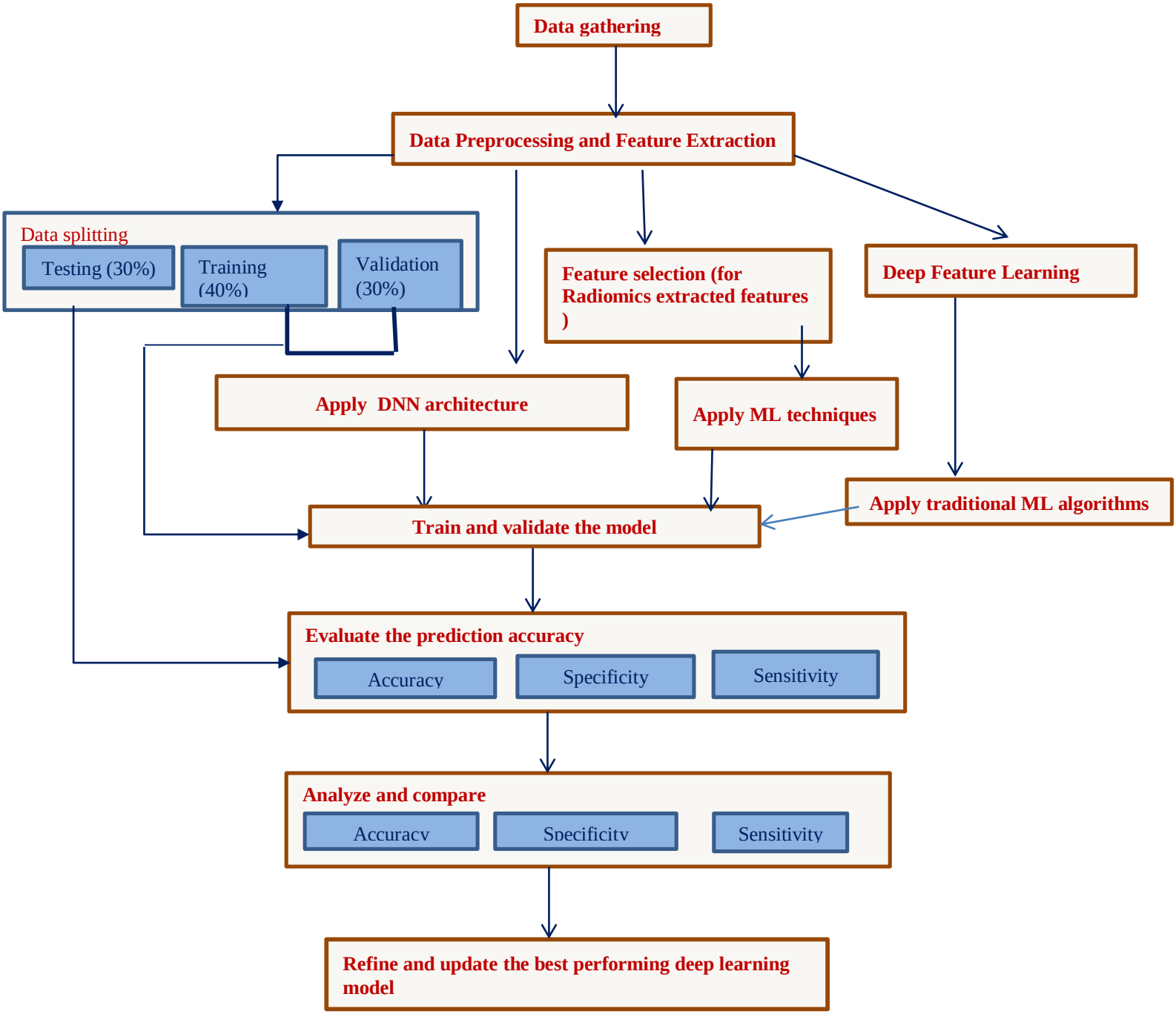
5. To analyze and compare the accuracy of different models developed through Steps 2, 3 and 4 above with respect to already existing models emerged as the outcome of previous research work as studied in Step 1

6. To refine and update the best performing deep learning model obtained as the outcome of analysis in Step 5 to build the final deep learning model with higher accuracy as compared to already existing models of Step 1 and validate the model.

6. Methodology to be adopted

The workflow is divided in these steps

- Data preparation: It includes
    - Data gathering: To gather Relevant Head and neck cancer images from Head and Neck cancer treatment centers and some open datasets.
    - Data preprocessing: Imaging data may be required to pre processed.
- Data splitting: We need to split the gathered data for testing, training and validation. 40% of the data would be used for training and 30% for validation and testing both.
- Build Models: Implementation would be followed in three phases
    - Phase 1: Identify and apply Deep neural architectures for prediction in Head and Neck Cancer.
    - Phase 2: Extract features through Radiomics and apply Machine Learning algorithms on these features for prediction in Head and Neck Cancer.
    - Phase 3: Apply machine learning algorithms on deep features extracted from deep learning.
- Train and validate the models.
- Evaluate the prediction accuracy, specificity and sensitivity for each phase.
- Analyze and compare the accuracy, specificity and sensitivity.
- Refine and update the best performing deep learning model.


Data gathering
Data Preprocessing and Feature Extraction
Data splitting
Testing (30%)
Training (40%)
Validation (30%)
Feature selection (for Radiomics extracted features)
Deep Feature Learning
Apply DNN architecture
Apply ML techniques
Apply traditional ML algorithms
Train and validate the model
Evaluate the prediction accuracy
Accuracy
Specificity
Sensitivity
Analyze and compare
Accuracy
Specificity
Sensitivity
Refine and update the best performing deep learning model

7. Expected Outcome

The proposed research work is expected to give following outcome:

- Successfully apply DNN architecture on imaging data to achieve a high accuracy in prediction and prognosis of Head and neck cancer based on its imaging data.
- A hybrid model that uses positives of CNN and other machine learning techniques for prediction and prognosis of Head and neck cancer.
- To be able to provide a model that applies machine learning algorithms on radiomics features for prediction and prognosis in Head and Neck cancer.
- Analyze and compare the models built on above mentioned architectures and the ability to select the best performing one to help oncologists in head and neck cancer treatment.

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Developing Deep Neural Network Models for Prediction and Prognosis of Head and Neck Cancer

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By

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Under the supervision of
Prof. Susmita Ray
Designation: Professor
Department of Computer Science and Engineering

ABSTRACT

Machine learning has provided a capability to learn from past experience and take decision for upcoming tasks. Machine learning with its advancements is showing very promising results in many real world applications includingmedical domain. Availability of automated systems in health care especially in cancer classification, prediction and prognosis estimation has become possible with the application of machine learning algorithms. Very extensively skilled and experienced practitioners are required for complete manual evaluation of all the biomedical data for cancer prediction and diagnosis. With the developments in hardware technology and imaging data availability, neural networks are showing very good results in automated learning from previous datasets and generating automated systems for cancer prediction and prognosis to help medical practitioners in decision making. The neural networks with deep layers, also known as deep neural networks are expected to extract features and learn with better accuracy. Recently a lot of research is carrying out in various common occurring cancer like kidney, prostate, lungs and oral cancer. Our proposed work aims at applying deep learning in radiological data of Head and Neck cancer region and achieving a good accuracy for prediction and prognosis in same. Radiomics is an upcoming field of extracting complex high dimensional features from medical

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